Restoration for High-overlapped Image Sequence with Composite Motion Blurs

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Abstract—Motion blur is a common degradation which usually brings difficulties to subsequent image process and analysis of a machine vision system. In this paper, an effective restoration scheme is proposed for high-overlapped image sequence with composite motion blurs which refer to the blurs caused during the exposure time by dual relative motions among the background of the scene, the moving objects and the scanning camera, resulting in additional local blurs in the global motion blurred image. Taking full advantages of high-overlapping ratios between neighboring frames, the global motion is estimated first to differentiate the local motion blurred region from the global blurred background. The local motion is then estimated from the extracted local motion blurred region. And the space-variant Point Spread Functions (PSFs) are calculated respectively based on different motion estimation results as the initiations for the Richardson-Lucy-based sectional restorations. A series of experiments and comparisons are carried out to testify the validity of the proposed method. The restoration results show that the proposed method can enhance the image quality effectively.

Index Terms—image restoration, composite motion blurs, space-variant PSF, motion estimation

I. Introduction

Motion blur is caused by the relative motion between the camera and the scene during the exposure time. It is one of the most common causes of image degradation and usually brings great difficulties to the following image process and analysis of a machine vision system. Restoration for motion blurred image is one of hot issues in image processing and analysis. It is widely demanded in many applications, such as communication system [1], intelligent surveillance [2], [3], remote sensing [4], medical research [5], etc.

Mathematically, motion blur is usually modeled as a convolution of Point Spread Function (PSF) which describes the response of an imaging system to a point input with the image represented by its intensities [6]. The degree of spreading in the image of this point input measures the blurs quantitatively with several parameters. According to the information amount of PSF, deblurring methods can be summarized into two categories, non-blind restoration with well estimated PSF and blind restoration with unknown PSF [7]. Most of the algorithms concentrate on the global blurs of static scenes, caused by camera shake or defocus. For the local blurred image, the restoration methods mainly address the situation that the camera and the background are fixed and only local moving objects cause the blurs. Actually, the degradation of an image is often characterized by space-variant motion blurs under a more general acquisition conditions, for example, the camera moves and the scenes contain different moving objects at different speeds as well. The restoration becomes more complex. Ref. [8] improved the Expectation-Maximization (EM) algorithm and combined with the region adaptive technique to handle the problem of identifying spatial variant blurs. Ref. [9] considered significant depth variations of scenes as one reason for causing space-variant blurs and proposed an algorithm for image restoration and simultaneous estimation of depth map from multiple images of the same scene blurred by camera motion. Ref. [10] addressed the space-variant image restoration for interlaced scan images and proposed a blind deconvolution algorithm by dividing the blurred image into odd field and even field and computing motion vector using an efficient block matching algorithm.

In this paper, we address the restoration for high-overlapped image sequence with composite motion blurs which refer to the blurs caused by dual relative motions among the scene, the moving objects and the scanning camera, resulting in additional local blurs in the global motion blurred image during the exposure time. An effective scheme is proposed by utilizing the high-overlapping ratios between neighboring frames properly and cooperating with PSF estimations for space-variant blurs. The global motion is estimated first based on phase correlation method to differentiate the local motion blurred region from the global blurred background. The local motion is then estimated from the extracted local motion blurred region. And the space-variant Point Spread Functions (PSFs) are calculated respectively based on different motion estimation results as the

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initiations for the Richardson-Lucy-based sectional restorations. The proposed method is simple to implement and its effectiveness is testified though a series of experiments.

The organization of this paper is as follows. Section II discusses the restoration problem we handled with and presents the proposed scheme for high-overlapped image sequence with composite motion blurs. Section III describes the details of global motion estimation and local blurred region extraction. Section IV introduces the calculations of PSF and sectional restorations for space-variant blurred images. Section V shows the experimental results and comparisons, and finally we conclude this paper in Section VI.

II. Problem Statement and Proposed Restoration Scheme

A. Problem Statement

In our image acquisition system, it is assumed that the original image sequences are captured by a camera settled on a horizontal stabled pan unit which can be controlled to scan the dynamic scenes at a uniform speed, as seen in Fig. 1 [11]. The captured video frames of the dynamic scenes are high-overlapped in the major scanning direction and seldom vertical movements. Due to the relative movement between the camera and the scene, the motion blurs are inevitable during the exposure.

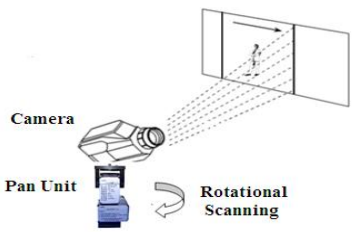


Fig. 1. Schematic working process of image acquisition system.

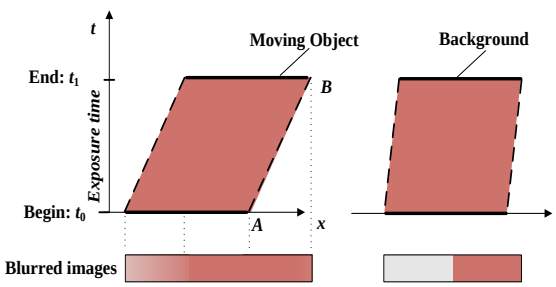


Fig. 2. The formation of composite motion blurs

The composite motion blur is especially caused by the moving object in the dynamic scene. Its formation principle is shown in Fig. 2. The global motion blur of the background exists during the exposure time [t_0, t_1]. The local motion blur is occurred with different blurring strength compared to the background blur when the object image moves from *A* to *B*. The composite motion blurs are then formed. The local moving object stresses the blur if its moving direction is opposite to the rotational orientation of the camera, i.e. the relative motion direction is the same as the global motion direction, or deduces the blur in otherwise. The traditional global restoration algorithm would be often locally failed since the PSF of the composite blurred image is regionally various. In our work, an effective restoration scheme is designed for solving the composite motion blurs under the rotational capture conditions.

B. Proposed Restoration Scheme

Due to the high-overlapping ratio between neighboring frames, the repetitive information is utilized to estimate the global motion and to determine the local motion blurred amounts and the positions of moving objects. The proposed restoration scheme for composite motion blurred image is shown in Fig. 3.

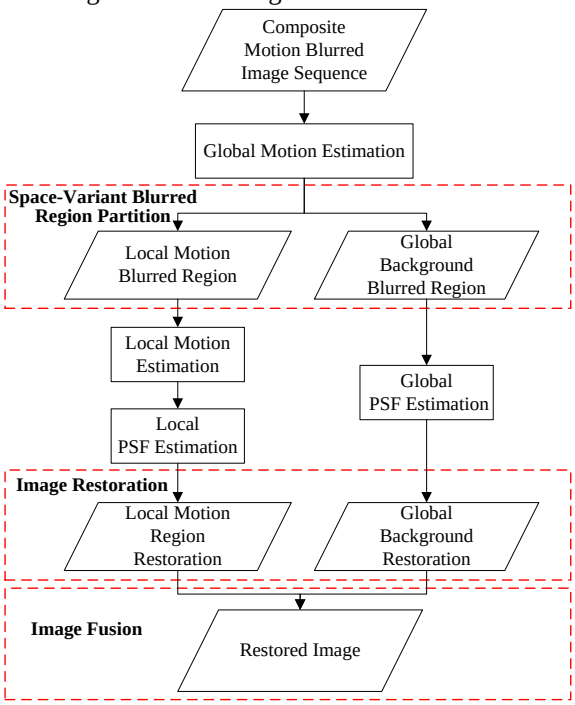


Fig. 3. The proposed restoration scheme for high-overlapped image sequence with composite motion blurs

Global motion is estimated first to differentiate the local motion blurred region from the global blurred background. The local motion is then estimated from the extracted local motion blurred region. The space-variant PSFs are calculated respectively based on different motion estimation results associating with prior system knowledge, e.g. exposure time, frame rate, etc. Then different blurred regions are restored separately and fused into the final restored image. More technique details are going to be explained in the following sections.

III. Global Motion Estimation and Local Blurred Region Extraction

A. Global Motion Estimation based on Phase Correlation

Traditional motion estimation algorithms are sensitive to intensity variance, noises or other effects of external

capturing factors. Phase correlation is a widely used method of image registration based on fast frequency-domain approach. It utilizes the translation property of the Fourier transform, i.e. shifting a signal in time domain introduces linear phase difference in frequency domain, to estimate the relative offsets between two similar images. The offsets between images are obtained by calculating the center position of the inversed Fourier transform of their cross-power spectrum [12]. It only utilizes the phase information of the cross-power spectrum in motion estimation, which reduces the dependence on space contents of images. It shows strong anti-interference ability and high estimation accuracy. Accordingly, in our work, we adopt phase correlation method for global motion estimation.

Given $f_1(x,y)$ and $f_2(x,y)$, two neighboring images with composite motion blurs, their corresponding Fourier transforms are $F_1(u,v)$ and $F_2(u,v)$. If the displacement between $f_1(x,y)$ and $f_2(x,y)$ is (x_0,y_0), i.e.:

$$f_2(x,y) = f_1(x+x_0, y+y_0) \tag{1}$$

Their Fourier transform satisfies:

$$F_2(u,v) = F_1(u,v)e^{j2\pi(ux_0+vy_0)} \tag{2}$$

The cross-power spectrum of these two images becomes:

$$Q(u,v) = \frac{F_2(u,v)F_1^*(u,v)}{\left|F_2(u,v)F_1^*(u,v)\right|} = e^{j2\pi(ux_0+vy_0)} \tag{3}$$

where $F_1^*(u,v)$ is the conjugation of $F_1(u,v)$. Taking the inverse Fourier transform of (3) can generate an impulse function $\delta(x_0,y_0)$ whose center determines the displacement between the two images.

In order to detect the offsets in sub-pixel level, downsamplings by integer factors M and N along x and y directions are conducted. The cross-power spectrum after downsamplings becomes:

$$Q'(u,v) = \sum_{m=0}^{M-1}\sum_{n=0}^{N-1} H_{mn}(u',v')e^{j2\pi(u'x_1+v'y_1)} \tag{4}$$

where
$$u' = \frac{u+m}{M}, v' = \frac{v+n}{N} \tag{5}$$

and H_{mn} is a downstream sampling Sinc filter. The inverse Fourier transform of $Q'(u,v)$ is a 2D Sinc function whose center locates at $(x_1/M, y_1/N)$, i.e.:

$$C(x,y) = \frac{\sin(\pi(Mx+x_1))}{\pi(Mx+x_1)}\frac{\sin(\pi(Ny+y_1))}{\pi(Ny+y_1)} \tag{6}$$

The offsets (x_1,y_1) between two images in sub-pixel level can be then obtained by calculating the center position of $C(x,y)$.

B. Extraction of Local Motion Blurred Region

After global motion estimation, the overlapped regions between neighboring frames can be determined according to the results by aligning neighboring background first, and the local motion blurred regions can be located as well due to the higher motion differences caused by obvious moving objects in the scene. The extraction process is as follows.

Each frame $I(t_i)$ is first aligned to its following one $I(t_j)$ combined with the global motion estimation result. Then the local difference image d_{ij} is obtained by subtracting these aligned images, $I'(t_i)$ and $I(t_j)$, as shown in Fig. 4. The thresholding is applied. Only the significant motion difference is reserved, i.e.:

$$d_{ij}(x,y) = \begin{cases} 1 & if \left|I'(x,y,t_i) - I(x,y,t_j)\right| > T_g \\ 0 & otherwise \end{cases} \tag{7}$$

where (x,y) is the point in the overlapping region between $I(t_i)$ and $I(t_j)$. The pixels in the difference image with non-zero values correspond to the regions that discernible changes occurred due to the movement of objects.

Moreover, morphological opening and closing operations on the local difference image d_{ij} are involved to exclude the isolating detected pixels. The local motion blurred region caused by the moving object is then identified by projecting the post-processed d_{ij} onto both horizontal and vertical directions and judging non-zero ranges on the x-axis and the y-axis. The local motion of the extracted local motion blurred region can be estimated by the phase correlation method in the similar way as well and compensated the global motion estimation at last.

IV. PSF Estimations for Space-Variant Blurs and Restorations

A. PSF Estimitions for Space-Variant Blurs

During the capturing process of the system, the camera settled on a controlled horizontal pan unit rotationally scans the scene at a uniform velocity. The global blurred background is considered as uniform linear motion blurred image due to this motion mode of the camera. The local blurred region can be also deemed as linear motion blurred image but in various motion amounts since the neighboring frames are highly overlapped.

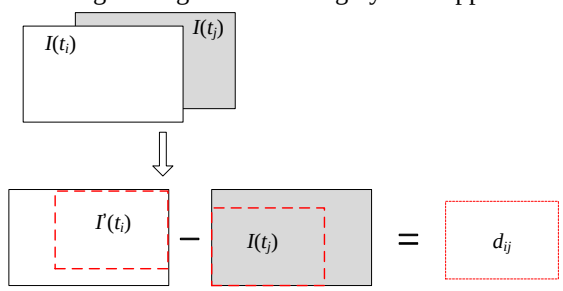


Fig. 4. Schematic diagram for local motion difference image extraction.

Let θ represent the blur angle between the motion orientation and the x-axis, and L denote the blur length, then the PSF model of linear motion blurs can be expressed as follows [13]:

$$h(x,y)=\begin{cases}1/L & y=x\tan\theta, 0\le x\le L\cos\theta\\ 0 & y\ne x\tan\theta, -\infty\le x\le\infty\end{cases} \quad (8)$$

If given the camera capturing frame rate P, the exposure time T, and the motion estimation results (X, Y), the blur length L and the blur angle θ become:

$$L=\frac{\sqrt{X^2+Y^2}}{1/P}\times T=\sqrt{X^2+Y^2}\times P\times T \quad (9)$$

$$\theta=\tan^{-1}\frac{Y}{X} \quad (10)$$

It can be seen that if the blur angle θ and the blur length L are determined, the PSF is then obtained. And the blurred image can be restored via the estimated PSF. In our case, for the space-variant blurs, the PSF parameters are estimated respectively. The PSF parameters of the global background blur is derived from (9) and (10) based on the global motion estimation result, so do the PSF parameters of the local motion blur based on the local motion estimation results.

B. Restorations based on Richardson-Lucy Algorithm

After receiving regional space-variant PSF parameters, the restoration for multiple motion blurs is then conducted separately.

Richardson-Lucy (RL) algorithm is one of the most widely used image restoration algorithms in aerial photograph, medical imaging research, etc. It is a non-linear iterative method, deriving from Bayes theory, first developed by Richardson and Lucy in the 1970s [14]. The image deblurred by RL algorithm usually presents better result, and its restoration process can avoid the strict restriction on accurate PSF which is demanded in Wiener filtering, inverse filtering or other restoration methods. We bring the previous estimated PSFs into the initial iteration to reduce the iteration times and access more precise PSF progressively.

It supposes that the image and noises both satisfy Poisson probability statistic model. Let $f(x,y)$ be the hoped deblurred image, $h(x,y)$ the PSF, $g(x,y)$ the motion blurred image and $n(x,y)$ the additive noise. According to the degradation model of motion blur image, we can get that:

$$g(x,y)=f(x,y)\otimes h(x,y)+n(x,y) \quad (11)$$

where "$\otimes$" is the convolution operation.

The restoration task is to approximate the clear image $f(x,y)$ though the blurred image $g(x,y)$. The RL algorithm can be considered a maximum likelihood solution using the Poisson distribution to model the likelihood probability [15]. For the Poisson distribution, the likelihood probability of $f(x,y)$ can be expressed as:

$$P(g(x,y)\mid f)=\prod_{(x,y)\in D}\frac{(f\otimes h)^g\exp\{-(f\otimes h)\}}{g!} \quad (12)$$

The maximum likelihood solution of image $f(x,y)$ is obtained by minimizing the following energy function:

$$f^*=\arg\min_f E(f) \quad (13)$$

where $E(f)=\sum\{(f\otimes h)-g\log[(f\otimes h)]\}$ (14)

Calculating the derivative of (14) and supposing the normalized blur kernel $\sum h(x,y)=1$, the iterative update rule is then obtained as follows:

$$f^{t+1}=f^t[h^*\otimes\frac{g}{f^t\otimes h}] \quad (15)$$

where h^* is the transpose of h that flips the shape of h upside-down and left-to-right, and t is the iteration index. For the initial guess, the algorithm can start with $f^0(x,y)=g(x,y)$.

During the above iterative convolutions, ring artifacts are easily generated since the pixel values, outside the margins of the image, are unknown. We apply symmetric extension in 8 orientations to fill the unknowns for decreasing the propagation of ringing effects and further amplification of image noise during the increase of iterations.

The restorations for composite motion blurred image can be conducted regionally according to the estimated space-variant PSFs based on the above RL algorithm. At last, the local restored image is inserted into the global restored background image and fused together. The final restoration image is then formed.

V. Exprement Results

A. Implementation Details

In order to illustrate the implementation details of the proposed restoration method, we present a typical sequence of composite motion blurred images which was captured by the uniform rotated camera at 20 fps frame rate with 1.6ms exposure time for an instance, as shown in Fig. 5.

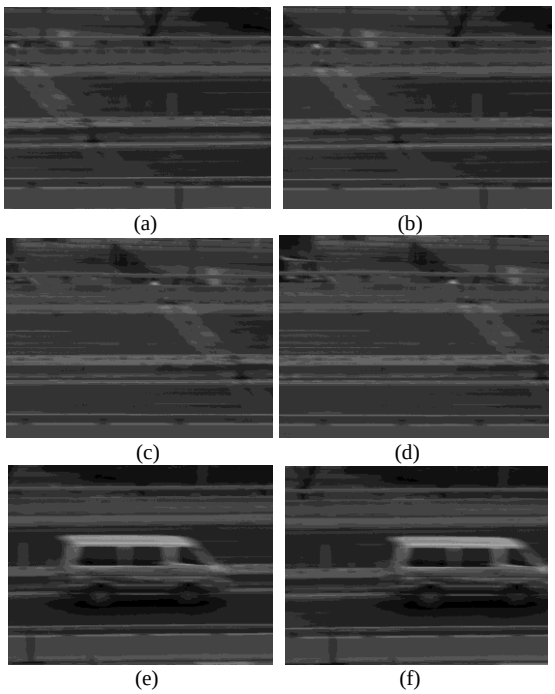
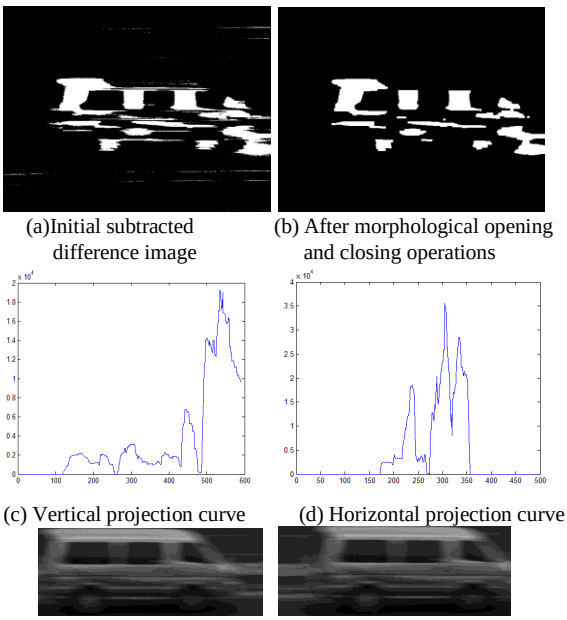


Fig. 5. Typical image sequence with composite motion blur.

The global motions were estimated first by phase correlation. The motion estimation results are listed in Table I. The major motions lied in *x*-axis since the camera rotated stably in horizontal direction, seldom vertical vibrations. It can be seen from Table I that phase correlation method estimates the global motion effectively for the high-overlapped blurred image sequence if without local disturbance of moving object, as seen the displacement differences between (a)→(b) and (c)→(d) is no more than 0.8%, which was supposed almost the same displacement from (a) to (b) as that from (c) to (d) since the capture interval and the exposure time were set fixed. Nevertheless, due to the appearance of moving object, as in (e) and (f), the global motion estimation result of (e)→(f) fluctuated a lot. The displacement differences between (c)→(d) and (e)→(f) was larger than 120%. Owing to this characteristic, hence, the extraction of local motion blurred region was then triggered on. The process and results are shown in Fig. 6.



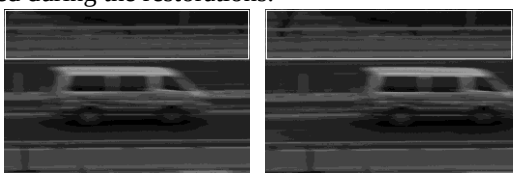
(a)Initial subtracted difference image (b) After morphological opening and closing operations

(c) Vertical projection curve (d) Horizontal projection curve

(e) Local motion blurred region of Fig.5 (e) (f) Local motion blurred region of Fig. 5 (f)

Fig. 6. The extraction process of local motion blurred regions.

After locating the moving object, the global motion can be rectified by the left partial images as seen in Fig. 7, labeled in the white rectangles. The rectified global motion and local motion estimation results of Fig. 5(e) and Fig. 5(f) are listed in Table II, in which the local estimated motion had been compensated the global background motions since the extracted moving regions were aligned by the global motions in advance. Then, the space-variant PSFs were obtained, associating with the capture parameters, as seen in Table III. They were taken as the initials for RL iterations to restore the composite motion blurred image regionally. The RL iteration results of sectional restorations are shown in Fig. 8. With the increase of iterations, the restoration results are better, but the ringing artifacts getting worse. According to the blur length, the symmetric extension in 8 orientations was implemented, as shown in Fig. 9, to weaken the effects. Considering the efficiency of the algorithm, only the central part of the extension image, in red rectangle, was selected during the restorations.



(e') (f')

Fig. 7. Partial images for background motion estimation excluding local moving object.

TABLE I: IMAGE SEQUENCE MOTION ESTIMATION RESULTS OF FIG. 5

Neighboring Images	Offset in *x*-axis	Offset in *y*-axis
(a)→(b)	59.00	-2.9
(c)→(d)	59.45	2.9
(e)→(f)	130.7	-2.2

TABLE II: SPACE-VARIANT MOTION ESTIMATION RESULTS WITH COMPOSITE MOTION BLURS

Motions	Offset in *x*-axis	Offset in *y*-axis
Global background from the partial image	60.35	-3.1
Local moving object Region	129.55	0.90

Table III: PSF Parameters of Space-Variant Blurs

(e)→(f) in Fig. 5	Blur length *L*	Blur angle θ
Global background blur	19.3375	-2.9405°
Local motion blur	41.4570	0.3980°

(a) 10 iterations (b) 15 iterations (c) 20 iterations

Fig. 8. Iterative restorations of global background and local moving region by RL algorithm.

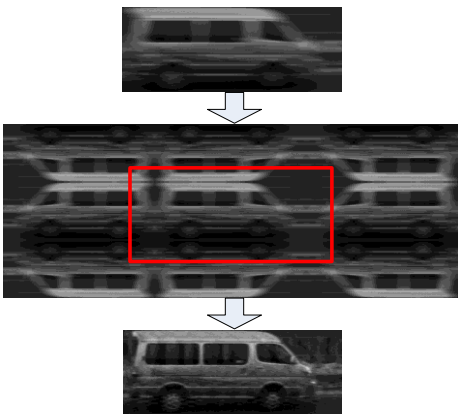


Fig. 9. Local restoration with symmetric extensions to weaken ringing artifacts.

Finally, the global background restoration and the local moving region restoration were fused together, and the deblurred result is shown in Fig. 10.

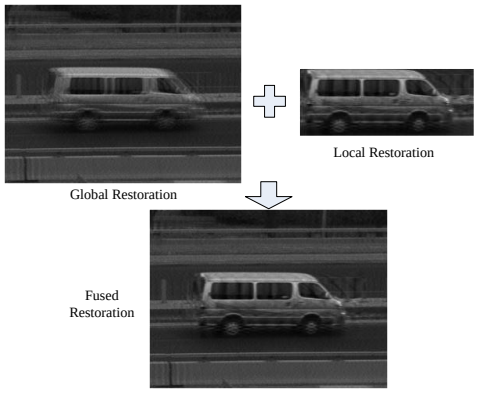


Fig. 10. The final deblurred result.

B. More Experiments and Comparisons

In order to testify the performance of the proposed method for the composite motion blurred image, we carried out a series of experiments and compared with other 3 representative types of restoration algorithms, the traditional non-blind restoration method based on Wiener filtering (k=0.01) [16], a robust motion deblurring algorithm based on two-phase kernel estimation [17] and a blind iterative restoration algorithm based on genetic algorithm [18].

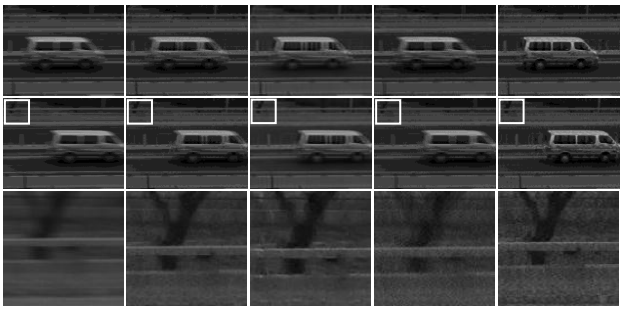
Some comparison experimental results are shown in Fig. 11 ~ Fig. 15, in which (a)s are the original blurred sequences, (b)s are the restoration results of Wiener filter, (c)s are the results of algorithm in [17], (d)s are the results of algorithm in [18], and (e)s are the results of the proposed method in this paper. The first rows are the previous frames of blurred image sequences and the corresponding results of different restoration algorithms. The second rows are the next following frames and their restoration results. The third rows are the enlargements of the second rows of the white squares for observing in details.

Wiener filtering, as a widely used non-blind global deconvolution algorithm, can restore the static backgrounds nicely according to the global PSF estimation, as seen Fig. 11(b) ~ Fig. 14(b). Nevertheless, the restorations for the moving objects were not satisfied, especially when multiple moving objects exist, the ringing artifacts of the moving object whose blur was partly canceled by the relative motion were serious, as seen in Fig. 15(b), the car in silver-white color. For the composite motion blurred image, Wiener filtering cannot handle the background blur and the local motion blur at the same time.

The algorithm of [17] belongs to the methods using blur kernel for restorations. It estimated the parameters of PSF first, and then restored. The moving objects made the estimated motion blur kernel incline to them. The estimation error increased greatly especially for the scenes containing multiple moving objects, e.g. scene #5, in which the kernel inclined to the silver-white moving car, resulting in seldom restoration for others.

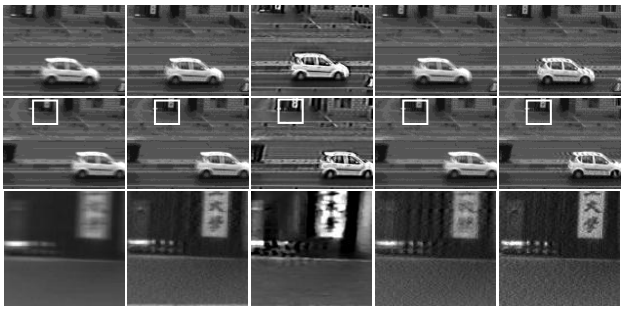
The algorithm of [18] combined the PSF estimation with restoration iterations simultaneously. The PSF parameters were corrected gradually during every step of iterations. It lacked in using the priori knowledge of the system, plus the impact of composite motions, resulting in inaccurate estimations of the PSF. The restoration results were dissatisfied, neither the background nor the moving objects, as seen Fig. 11(d) ~ Fig. 15(d).

The proposed method restored the background and moving objects respectively with the estimated space-variant PSFs as the initiations of the RL algorithm. The PSFs were estimated by locating the local motion blurred region via efficient motion estimations. The processing scheme takes full use of the repetitive information among high-overlapped image sequence and the prior system knowledge to address the space-variant blurring problem. From the comparison experiments, it can be seen that the image qualities were enhanced globally. It is superior to other compared algorithms both in global background restoration and local moving object restoration.



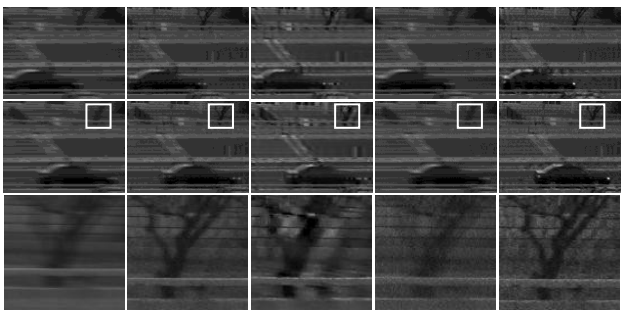
(a) (b) (c) (d) (e)

Fig.11. Restoration results of scene #1.



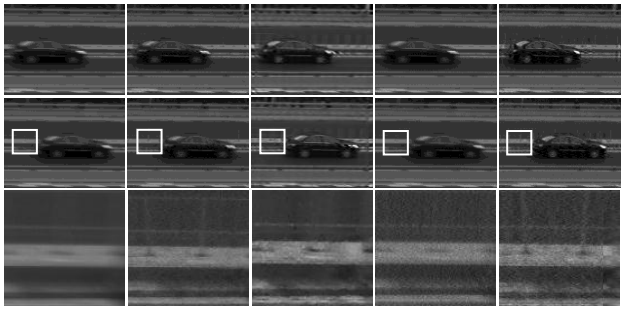
(a) (b) (c) (d) (e)

Fig. 12. Restoration results of scene #2.



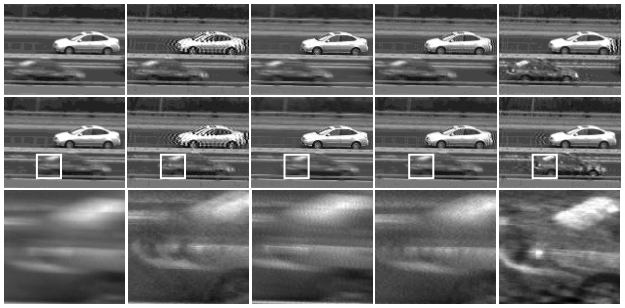
(a) (b) (c) (d) (e)

Fig. 13. Restoration results of scene #3.



(a) (b) (c) (d) (e)

Fig. 14. Restoration results of scene #4.



(a) (b) (c) (d) (e)

Fig. 15. Restoration results of scene #5.

VI. Conclusions

Composite motion blur often occurs in many machine-vision-based application systems if existing multiple relative motions among the content of the scene, the background and the camera. In this paper, an efficient image restoration method for high-overlapped image sequence with composite motion blurs is proposed. It can greatly enhance the image quality by utilizing the high-overlapping ratios between neighboring frames properly and cooperating with space-variant PSF estimations. The work of this paper is high of practical significance. The future research will focus on the blending between the restored background and the local motion deblurred regions to smooth down the edge artifacts caused by non-uniform PSFs.

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